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Brand Procurement on Vertical Relationships
with Brand Manufacturers and on Market Equilibrium

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Determining the Impact of Retailer Store Brand Procurement on Vertical Relationships with Brand Manufacturers and on Market Equilibrium †

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Abstract

This paper investigates how a retailer's store brand supply source impacts vertical pricing and supply channel profitability. Using chain-level retail scanner data from major supermarkets in Boston prior to the leading retailer's divestiture of its store brand milk processing to a major brand manufacturer I estimate a random coefficients logit demand model employing a Bayesian estimation approach. Bayesian decision theory is applied to select from a set of pricing games the one most likely for the data sample analyzed. Results from this analysis indicate that the empirically valid model has the pre-divested retailer integrated into the processing of its own milk and takes as given the wholesale price of brand milks while competing retailers have non-linear pricing contracts with brand manufacturers who produce their store brands. This model is matched against a series of counterfactual simulations as a baseline. The counterfactual simulations consider the eventual divestiture of store brand milk processing by the leading retailer

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to a major brand manufacturer as well as two fictional markets where store brands are no longer offered and optimal nonlinear pricing breaks down making way for a double marginalization outcome. Simulation results indicate that the divesture likely improved profitability and reduced retail prices by eliminating double marginalization.

1 Introduction

In some cases retailers produce their own store brand products and in other cases they contract production of their store brands to manufacturers who supply similar branded products. This paper demonstrates that store brand procurement by supermarkets determines strategic pricing arrangements with brand manufacturers. Both theoretical and empirical research finds that the marketing of store brands by retailers eliminates double marginalization, reduces retail prices on leading brands, and increases channel profits and consumer welfare. Store brand marketing as a competitive strategy yields larger profit flow to the retailers generated by larger margins on the leading manufacturer brands and the sale of store brands themselves (Mills, 1995; Scott-Morton & Zettelmeyer, 2001; Chintagunta & Bonfrer, 2002). This paper employs a structural modeling approach to analyze the vertical relationships of retailers and manufacturers when a leading supermarket processes its own store brand product and other supermarkets procure own-labeled milk from brand manufacturers.

The investigation examines chain-level retailer scanner data for white fluid milks sold at major supermarkets in Boston from March 1996 to July 2000. Specification of pricing models for empirical testing requires estimation of an demand model. The flexible random coefficient logit demand model of Berry, Levinsohn, and Pakes (1995) is applied and estimated using the Bayesian approach of Jiang, Manchanda, and Rossi (2009). Parameter estimates are used to calculate implied retailer and manufacturer margins under the alternative vertical pricing arrangements.

Channel costs are computed from the implied margins and regressed on input prices. Bayesian decision theory selects the "best fitting" channel marginal cost model. If there are different pricing relationships between supermarkets that manufacture their own store brands and supermarkets that source store brands from brand manufacturers then the best fitting model will reveal them.

After finding empirical evidence that testifies that there are differences in pricing arrangements for supermarket that produce their own store brands I consider counterfactuals that examine differences to equilibria that result when the retailer divest processing of this store brand products to brand manufacturers. One of the counterfactuals considers the divestiture of the leading retailer's store brand processing to the leading brand manufacturer. The other two counterfactuals investigate the market without store brands. In one case retailers and manufacturers engage in nonlinear pricing. In the other case linear pricing leads to the double marginalization outcome that store brand provision is thought to eliminate. I compute the percent difference in price, market share, and consumer surplus between the selected market model and each counterfactual market model to evaluate the impact of store brand supply source.

Mills (1995) presents a rigorous model that demonstrates store brands are instruments for a retailer to overcome the well-known double marginalization problem present in distribution channels. Store brand provision allows the retailer to extract profit from the vertical channel and lower prices. Steiner (2004) similarly argues that the unique position of store brands constrain the market power of national brands in ways that their horizontal competitors cannot. Steiner (1993) describes a vertical structure where store brands generate countervailing retailer power and improve welfare. However neither of these papers considers how the retailers supply source impacts these effects.

An empirical analysis by Raju, Sethuraman, and Dhar (1995) finds that store brands increase category profits for retailers and find that this is particularly true when a category has several brands. Chintagunta and Bonfrer (2002) examine the introduction of a store brand into a category by estimating demand conditions before and after its introduction at a single retailer. They observe wholesale prices paid by the retailer and use them to gain intuition on vertical conduct in the market. For demand they investigate the changes in preferences under the two market regimes, before and after the introduction of the store brand. On the supply side they measure the effects of the new entrant's store brand on the actions between retailer and manufacturer. However they use a conduct parameter approach and do not explicitly formulate and test alternative pricing games.[1]

Modeling the vertical channel allows the researcher to identify the nature of vertical pricing conduct between manufacturers and retailers. These models link manufacturers wholesale pricing moves down to some form of retailer pricing conduct. Sudhir (2001) demonstrates the need to

[1] See Corts (1998) for critiques of conduct parameter approaches.

accurately model vertical strategic interactions along with horizontal strategic interactions when using retail level data. Villas-Boas and Zhao (2005) investigate the ketchup market in a Texas market and reveal bias that results by ignoring endogeneity of demand, and model the supply side with the profit maximizing decision of retailers and manufacturers. Villas-Boas (2007) outlines conditions that allow data on retail price, retail quantities and input prices at the two stages in the market channel to identify retailers' and manufacturers' vertical pricing conduct. This method allows one to investigate interactions in the market channel pricing using retail level prices without observing wholesale prices. However she analyzes retail conduct for two chain stores and a small retailer, a total of 3 locations, and a set of manufacturers. A thorough investigation of product the market requires one to study a robust cross section of firms at each level of the channel. In this paper I analyze vertical conduct in a market that has four retail chains, a total of 187 locations, each chain with a store brand, and two brand manufactures that sell in all four retailers. Bonnet and Dubois (2010) empirically investigate vertical contracts between retailers and manufactures using retail data on bottled water collected from retail chains in France. They extend previous work by considering non linear vertical contracts that model two part tariffs with and without retail price maintenance.

Empirical models of the vertical channel estimated with retail scan data apply non-nested tests between competing models of channel cost to determine a "best fitting" model. Villas-Boas (2007) and Bonnet and Dubois (2010) use the tests of Smith (1992) and Voung (2002), Rivers and Voung (2002) respectively to determine the best fitting channel cost model. The tests they implement have two problems. One they are not transitive. Non-transitivity implies that the tests of channel pricing potentially offer inconclusive and inconsistent results. Applying the Bayesian framework directs the researcher to rank models according to posterior probability and select the model with the highest probability guaranteing transitivity. The second problem those two papers face is the identification strength on their non-nested testing approach. Testing models of channel cost rely on the decomposition of price into retailer markup, manufacturer markup, and channel cost, none of which are directly observed in retail scanner data. Therefore one requires exogenous variation in at least two of the three components to achieve identification. The previous literature does not exploit independent retailer specific variation in cost factors, implying their tests may not be identified, at least in an nonparametric sense.

This paper contributes to the existing literature in two ways. Primarily it provides a framework to analyze the impact of retailer store brand procurement on vertical pricing arrangements and documents the extent two which a retailer's supply source for store brands impacts market equilibria. As an additional contribution this paper improves the approach for selecting the best fitting model of supply channel pricing in two ways. First it overcomes the non-transitivity of the non-nested tests, typically applied, by using Bayesian decision theory. Second it exploits retailer level variation in product characteristics to establish identification of the tests for competing models of market conduct.

The remainder of this paper is organized as follows. Next it introduces the Boston fluid milk market and describes the data. Then it derives models for optimal retailer and manufacturer margins and describes the set of market structures tested as potential candidates. The fourth section presents the demand model, estimation approach, and method for model selection. The fifth section presents the estimation results and model selection results. The sixth section compares the market equilibrium for the selected model to the market equilibria that arise under the counterfactual markets. Finally, concluding remarks and suggestions for extending the research are made.

2 The Boston Fluid Milk Market and Data

2.1 Facts About the Market for Fluid Milk in Boston

The Boston supermarket industry is one of the most competitive, ranking 6th among all IRI defined marketing areas in the United States in grocery sales. 80% of food in Boston is sold though super markets. Four major chains operate in most of the market: Stop & Shop, Demoulas Market Basket, Shaw's, and Star Market. Stop & Shop is the market share leader and enjoyed a significant expansion during the study period. Stop & Shop captured this share from residual retailers while the other supermarkets maintained their market share position.

Stop & Shop is owned and controlled by European retailing giant Royal Ahold. Shaw's is owned and controlled by a British company named Sainsbury PLC. Star Market was highly leveraged but in the third quarter of 1998 they were bought out by Sainsbury PLC. After this point Shaw's and Star Market continued to operate under their respective banners. Since consumers viewed these supermarkets as different retailers they are considered separate firms for this analysis. The fourth supermarket, Demoulas, is a privately held retail chain.

Within the greater Boston IRI area Star Markets has larger presence in the inner city areas with relatively smaller retail outlet size. Demoulas are primarily located in suburbs north of Boston proper. Shaw's and Stop & Shop are scattered throughout the market area, however Shaw's has fewer stores in the urban core.

The Boston fluid milk market has two primary brands, Garelick and Hood. Each retailer sells a store brand. Store brands hold a dominant market share position within each retailer, this is particularly true at Demoulas and Stop & Shop. Other milks on retailer shelves are fringe specialty milks such as lactose intolerant and organic brand alternatives, whose popularity had not yet gained momentum in the late 1990's.

The Garelick brand manufacturer, Suiza, is the largest in the Boston area followed by Hood. The store brand milk sold at Demoulas, Star Market, and Shaw's is processed at Suiza plants. The store brand milk sold at Stop & Shop was processed at a retailer owned plant. As of June 2000 Stop & Shop closed this plant and has since procured its store brand milk from Suiza's processing plants.

2.2 The Data

The Information Resources Inc.(IRI) Boston market level data for each of four chains used in this study has many chain level variables including prices and quantity, and it covers 58 quad week periods beginning March 1996 and ending July 2000. The class one raw milk price data are from federal milk market order one publications. Data on supermarket characteristics for each chain come from Spectra Marketing and span the same time period as the scanner data in quarterly observations, this data set also reports a figure for sales per square foot. Per capita income and population data have been collected from annual editions of Market Scope. Data on electricity and diesel fuel cost are from the Energy Information Administration.[2]

[2]Spectra Marketing is a sister company of A. C. Nielsen. All marketing data are available from the University of Connecticut, Food Marketing Policy Center.

Exploring chain level data implies uniform pricing behavior across retail outlets within a chain in a market such as Boston. Generally for an advertised product such as milk this is the case within a market area. Chains price uniformly to avoid the criticism that they are price gouging particular urban neighborhoods. We aggregate IRI stock keeping unit (sku) data to the brand level for each chain.[3] We control for the impact of package size differences on demand by including a units per volume variable in our demand specification. Aggregation over different fat levels, for a given brand of white fluid milk is a reasonable practice because the retailers we consider engage in flat pricing of milk across fat levels (Cotterill, Rabinowitz, Cohen, Murphy, & Rhodes, 2007).

The same brands at different retailers are different products. For this reason our demand specification includes attributes of the retail chain as a characteristic of the products purchased in that retail chain. Using Spectra Marketing data one has the following retailer characteristics: pharmacy, bank, fresh fish counter, deli, and salad bar. This approach recognizes that a chain can brand it self by developing a unique array of services and products including a broad high quality line of store brands. Also chain specific data generate exogenous variation in retail margins that permit us to identify the non-nested tests of channel pricing conduct. Bonnano and Lopez (2009) report that the consumer demand for fluid milk is influenced by one stop shopping attributes of supermarkets including breadth and depth of services offered. In the Spectra data one knows whether a specific store in the Boston market has the service or not. Using this information one can calculate the proportion of stores in the chain offering the service in each time period. Due to collinearity in the service data I use principal component analysis to identify two orthogonal services. To generate a non-food service variable I take the product of the propensity measures for those services, the same procedure is executed to generate a food service variable.

Table 1 reports summary statistics for chain specific brand price, market shares, and group shares. Hood has the highest per gallon prices across all chains followed by Garelick then private label. Among the retail chains Star Markets, located in the urban core, has on average the highest milk prices followed by Stop & Shop, Shaws, then Demoulas. Stop & Shop has the largest share of fluid milk sales with 18%, and they lead in store brand sales with 12.6% while Demoulas is a close second with 11.1%. Store brand dominates sales within Demoulas at 89.8% whereas Star markets

[3] Skus identify package sizes and different products within a brand.

store brand milk sales only make up 52.3%.

Table 2 has summary statistics for three other control variables. Weighted price reduction is a variable measuring price promotion of a given brand in the supermarket. It is the percent reduction in price from the suggested retail price when price is reduced. This variable controls for price promotional activities. The “share of skim to whole milk sold” controls for the aggregation of the different butter fat content milks which may influence demand if consumers are health conscious. A value greater than 1 reveals that a greater share of skim or low-fat milk was sold for the given product than whole. “Units per volume” which is the average number of units sold per gallon and controls for container size.

Table 3 reports the Spectra Marketing data on store characteristics for each chain. Stop&Shop had on average approximately 70 stores in the Boston metropolitan area during this period, Shaws had approximately 46, Demoulas 32 and Star 19. Stop&Shop’s stores have the most retail space. Stop&Shop is also the leader in services especially in non-food services as compared to their competitors. Demoulas has the fewest services and Shaws and Star have similar amounts. Table 3 also has market level statistics for household income as well as channel input costs: the prices of raw milk, electric, and diesel. Note the typical price paid to farmers for a gallon of raw milk is $1.40 effectively half of the retail price.

3 Structural Model of the Supply Channel

This section introduces the supply models tested as candidates for the Boston fluid milk market. Strategic profit maximization is modeled at both the retail and manufacturer levels of the supply chain. Farmers supply milk at an exogenously set federal milk market order prices, so manufacturers secure it from a competitive input market. First I derive profit maximizing margins for retailers and then for manufacturers under linear pricing. Next I introduce a model for nonlinear contracts in the form of two part tariffs. Then I argue for a set of six empirical models tested as relevant candidates for the Boston fluid milk market.

3.1 Linear Pricing

Retailer

Assume there are N Nash Bertrand multi-product oligopolists competing in a retail market and each retailer maximizes category profit for sale of all branded and own-labeled fluid milk products. Each retailer's milk profit function, for a particular time period, is:

$$\pi_r = \max_{p_j \forall j \in \mathfrak{S}_r} \sum_{j \in \mathfrak{S}_r} [p_j - p_j^m - c_j^r] s_j(p).$$

$\mathfrak{S}_r$ is the set of products sold by retailer r, m indexes manufacturers and j indexes products. The first order condition, assuming a pure strategy Nash equilibrium in prices, is:

$$s_j + \sum_{k \in \mathfrak{S}_r} [p_k - p_k^m - c_k^r] \frac{\partial s_k}{\partial p_j} = 0. \tag{1}$$

The first order conditions can be stacked into a system of equations for each product at each retailer. The terms may be rearranged to solve for retailer margins. This linear system can be expressed in matrix notation:

$$p - p^w - c^r = -(T_r \times_{elt} \triangle_r)^{-1} s(p). \tag{2}$$

T_r is a matrix of ones and zeros that captures the products in the set $\mathfrak{S}_r$ by executing element-wise multiplication, $\times_{elt}$. In other words the retailers maximize their profits over products in their portfolio, hence its called the ownership matrix. Element $T_r(k, j) = 1$ if a retailer has both products k and j in their portfolio, and $T_r(k, j) = 0$ otherwise. $\triangle_{rt}$ is a matrix containing the derivatives of share with respect to retail price. This matrix is called the retailer response matrix and has the typical element $\frac{\partial s_j}{\partial p_k}$.

Manufacturer

Assuming that manufacturers set wholesale price upon observing retail price the manufacturer's profit maximization problem is written as:

$$\pi_m = \max_{p^m \forall j \in \mathfrak{S}_m} \sum_{j \in \mathfrak{S}_m} [p_j^m - c_j^m] s_j(p(p^m)).$$

Here $\mathfrak{S}_m$ is the set of products sold by manufacturer m. The resulting first order condition is:

$$s_j + \sum_{k \in \mathfrak{S}_m} [p_k^m - c_k^m] \frac{\partial s_k}{\partial p_j^m} = 0. \tag{3}$$

The manufacturer ownership matrix T_m is defined in a manner analogous to that of the retail ownership matrix. The elements of the manufacturer response matrix, $\triangle_m$, are the derivatives of product market share with respect to wholesale price, i.e. $\frac{\partial s_j}{\partial p_i^m}$. The matrix $\triangle_m$ contains the cross price elasticities of demand and the effects of cost pass through, these effects can be decomposed in the following manner by evoking the chain rule:

$$\triangle_m = \triangle_p' \triangle_r.$$

Here $\triangle_p$ represents the cost pass through and $\triangle_r$ contains own and cross price sensitivities of market share to retail price changes. $\triangle_r$ was introduced in the previous subsection. The matrix $\triangle_p$'s elements are the derivatives of all retail prices with respect to all wholesale prices, and have the general element $\triangle_p(k,j) = \frac{\partial p_j}{\partial p_k^m}$.

The elements of the matrix $\triangle_p$ are derived by totally differentiating, for a given product j, the retailer first order condition in equation 1:

$$\sum_{k=1}^{N} \underbrace{[\frac{\partial s_j}{\partial p_k} + \sum_{i=1}^{N} (T_r(i,j) \frac{\partial^2 s_i}{\partial p_j \partial p_k} (p_i - p_i^m - c_i^r)) + T_r(k,j) \frac{\partial s_k}{\partial p_j}]}_{g(j,k)} dp_k - \underbrace{T_r(f,i) \frac{\partial s_f}{\partial p_j}}_{h(j,f)} dp_f^m = 0.$$

Stacking these conditions for all $j = 1, 2, ..., N$ products together into a linear system, one has,

$$G dp - H_f dp_f^m = 0.$$

The matrix G has general element $g(j,k)$, and H_f is an N-dimensional vector with general element $h(j,f)$. Rearranging terms implies the vector,

$$\frac{dp}{dp_f^m} = G^{-1} H_f.$$

Horizontally concatenating H_f together for all products j, one has the desired matrix,

$$\triangle_p = G^{-1}H.$$

Collecting terms equation 3 is solved for the manufacturers' implied price-cost margins:

$$p_t^m - c_t^m = -(T_w \times_{elt} \triangle_m)^{-1} s(p). \tag{4}$$

3.2 Nonlinear Contracts: Two-part Tariff Pricing

Under two part tariff nonlinear optimal pricing contracts manufacturers set wholesale price equal to marginal cost and let retailers be the residual claimant. The manufacturer then extracts some share of profit with a fixed fee paid by retailers. This fee can be recovered in many ways including product procurement contracts in particular. The existence of an equilibrium in a common agency game for the two manufacturer two retailer case is proved by Rey and Vergé (2004), who also characterize equilibria under very general conditions on demand elasticities and profit function shape that follow from the law of demand.

Retailer

In the case of a two part tariff contract retail profit is:

$$\pi_r = \sum_{j \in \mathfrak{S}_r} [(p_j - p_j^m - c_j^r) s_j(p) M - F_j]. \tag{5}$$

The retailer pays a fee, F_j, to the manufacturer for selling the product j and maximizes profits by setting p_j optimally.

Manufacturer

Manufacturer m determines wholesale price, p_j^m, and recovers a fee, F_j, to maximize the profit function,

$$\pi_m = \sum_{j \in \mathfrak{S}_m} [(p_j^m - c_j^m) s_j(p) + F_j]. \tag{6}$$

Subject to retailer participation constraints, $\pi_r > \bar{\pi}_r$, for all retailers $r = 1, \ldots, R$, where $\bar{\pi}_r$ is the profit level for the retailer's outside option of choosing not to sell manufacturer m's product. Rey and Vergé (2004) show that the participation constraints must be binding otherwise manufacturer fees F_j would rise only to be bounded by the conduct of other manufacturers. Bonnet and Dubois (2010) show that the expression for F_j can be substituted into equation 6 to recover the profit for manufacturer m:

$$\pi_m = \sum_{j \in \mathfrak{S}_m} (p_j - c_j^r - c_j^w) s_j(p) + \sum_{j \notin \mathfrak{S}_m} (p_j - p_j^w - c_j^r) - \sum_{j \notin \mathfrak{S}_m} F_j] \tag{7}$$

This expression reveals that manufacturers internalize the full margins on their products but only the retail margins on other manufacturers products. The additional term $\sum_{j \notin \mathfrak{S}_m} F_j$ is constant for manufacturer m and consequently drops out of the profit maximization problem which implies that impled channel markup is:

$$p - c^r - c^w = -(T_r \times_{elt} \delta_r)^{-1} s(p). \tag{8}$$

Under this arrangement the retailer recovers profits of a vertically integrated structure for the j products in its portfolio and manufacturers recover a share of these profits in the form of fees, F_j, or contracted wholesale prices.

Villas-Boas (2007) and Bonnet and Dubois (2010) consider a case where retail margins are zero and manufacturers make pricing decisions and award retailers slotting fees for selling their product or engage in resale price maintenance. Bonnet and Dubois (2010) test this model for the French bottled water market as two part tariff pricing with resale price maintenance. This model will not be considered for the Boston fluid milk market owing to legal standards on retail price maintenance.

3.3 Empirical Models of Channel Pricing

An empirical test to select the best fitting vertical pricing model enables one to determine whether retailer store band procurement arrangements impact pricing relationship with brand manufacturers. This paper tests six distinct structural models of pricing conduct which are identified by implied channel margins from a set of pricing games. Specification of the ownership matrices, T_r

and T_w, determine markups and the various forms of channel conduct explored. For each channel structure the retailer and manufacturer response matrices remain unchanged. Each model of channel pricing is presented in turn.

Under the first model retailers set margins by maximizing profits over the set of products in their portfolio according to equation 2. Manufacturers set margins upon observing the retailer's price response function. This is a Manufacturer Stackelberg pricing game and a double marginalization outcome. The pair of optimal margins that identifies the pricing game are given by equations 2 and 4. The ownership matrices that give rise to these implied margins have element $T(k, j) = 1$ if a firm has both products k and j in their portfolio, and $T(k, j) = 0$ otherwise. This model includes manufacturers of store brands that maximizes profits independent of the retailer they package for in the same fashion brand manufacturers do.

In the second structure manufacturers of the branded products, Hood and Garelick, determine pricing on their brands taking into consideration the retailers response function. Store brands are procured by retailers at marginal cost. There is no change to the retail ownership matrix from the first model. The manufacturer ownership and response matrix now simply omits rows and columns corresponding to store brand products. This model is consistent with a market where the retailer is vertically integrated into the manufacturing process and manufacturers its own store brand, such as Stop & Shop was doing during the period we study, or simply that the retailer is able to buy milk at or very close to cost from a processor. The latter scenario is typical when a branded manufacturer's processing plant wants to increase production to exploit economies of scale. Steiner (2004, p.113) cites research on private milk bargaining where this has been the case.

The third structure models manufacturer tacit collusion and retail integration into store brand procurement. This implies that the colluding entity has joint ownership over branded products. This model specifies a manufacturer ownership matrix that is unity for all manufacturer brands. The retailer ownership matrix remains unchanged.

For the fourth structure I test the nonlinear optimal pricing contract described in the previous subsection. With my retail scanner data the fee, F_j, cannot be recovered because wholesale prices are not observed. This means that the proportion of channel profits recovered by retailers versus manufacturers is not identified. Nevertheless the form of vertical pricing conduct can be. This structure is achieved from a modeling standpoint as setting $p_t^m = c_t^m$, as in equation 8. Definition of the retail ownership matrix remains unchanged. This structure arises when a channel captain or category manager is employed by retailers to work with manufacturers to improve efficiency in the channel (i.e. reduce double marginalization in the channel) and determine an optimal marketing mix at retail.

The fifth structure models colluding retailers, vertically integrated store brand procurement by retailers, and brand manufacturers that set wholesale price after observing the retailers' price reaction functions. To model this structure the retailer ownership matrix is unity for every element. The manufacturer's ownership matrix is the same as the second structure. As an empirical matter the market is dominated - in market share - by a single retailer, Stop & Shop, who could potentially lead other retailers to follow its pricing practices. Such a scenario is consistent with the fifth structure.

For the sixth structure I advance a hybrid model. One retailer is vertically integrated into the processing of its store brand milk and takes as given prices on brand manufacturer milks. Manufacturers price their brands sold to this retailer upon observing retailers' price reaction functions. The remaining retailers engage in the nonlinear optimal pricing contracts with the brand manufacturers described in the previous subsection. The vertically integrated retailer is Stop & Shop, who as one learnt in the previous section owned its own milk processing plant. It stands to reason that this is the most qualitatively valid model from an empirical standpoint. Following the data period under consideration Stop & Shop handed over production of its store brand milk to the Garelick brand manufacturer in exchange for a preferred procurement contract. During the data period the other retailers in the market procured their store brands from Garelick manufacturing plants.

4 Demand Specification, Estimation Approach, and Supply Model Selection

To compute the margins implied by the models presented in the previous section a model of demand must be specified and estimated. To begin the section introduces the random coefficients logit demand model of Berry et al. (1995) that is applied. Next it explains how the posterior model is specified for the Boston market data examined by applying the method of Jiang et al. (2009). Then it explains the Bayesian decision theoretic approach employed for selecting the most likely channel supply model.

4.1 Random Coefficients Logit

The random coefficients logit allows consumers to differ in tastes for product characteristics. Introducing heterogeneity in this way allows for flexibility in substitution patterns overcoming the restrictive substitution patterns implicit in simple logit or nested logit demand models. Implied margins computed free of the preordained substitution patterns guarantee that supply model selection is not driven by a restrictive demand specification.

I specify the following linear version of the random utility model(RUM)

$$V_{ij} = X_j \beta^i - \alpha^i p_j + \eta_j + \epsilon_{ij} \tag{9}$$

i and j subscript individuals and products respectively. A product is defined as a unique brand - retailer combination. x_j is a vector of characteristics for product j, and p_j is the price of product j. η_j is an aggregate brand and retailer specific demand shock, or in other words, a time varying product attribute unobserved by the econometrician. It is assumed that ϵ_{ij} are distributed *i.i.d.* according to an extreme value type I distribution. There are J products and a zero utility outside option, *i.e.* a consumer has the option of not buying milk at any of the retailers. $[\beta^i, \alpha^i] \equiv \theta^i$ are marginal utility parameters assumed to vary over consumers and follow the multivariate-normal distribution, $\theta^i \sim N([\bar{\theta}, \Sigma)$.

The market share of product j as a function of the total group share is

$$\begin{aligned} s_j &= \int s_{ij} \phi(\theta^i | \bar{\theta}, \Sigma) d\theta^i. \\ &= \int \frac{exp(X_j \theta^i + \eta_j)}{1 + \sum_k exp(X_k \theta^i + \eta_k)} \phi(\theta^i | \bar{\theta}, \Sigma) d\theta^i \end{aligned} \tag{10}$$

where ϕ is the multivariate normal density. Predicted shares can be expressed in terms of mean utility, observing that $\theta^i = \bar{\theta} + \nu_i$, where $\nu_i \sim N(\mathbf{0}, \Sigma)$, s_j is expressed as:

$$s_j = \int \frac{exp(\mu_j + X_j \nu_i)}{1 + \sum_k exp(\mu_k + X_k \nu_i)} \phi(\nu_i | \mathbf{0}, \Sigma) d\nu, \tag{11}$$

where $\mu_j = X_j \bar{\theta} + \eta_j$.

The consumer share is given by, $s_{ij} \equiv exp(X_j \theta^i + \eta_j + \epsilon_{ij})/1 + \sum_k exp(X_k \theta^i + \eta_k + \epsilon_{ik})$, the own and cross-price responses of market share, s_j are

$$\frac{\partial s_j}{\partial p_k} = \begin{cases} -\int \alpha^i s_{ij}(1 - s_{ij}) \phi(\nu_i) d\nu_i, & \text{if j=k;} \\ \int \alpha^i s_{ij} s_{ik} \phi(\nu_i) d\nu_i, & \text{otherwise.} \end{cases} \tag{12}$$

Independence of irrelevant alternatives (IIA), implicit with the extreme value error assumption, dictates that consumers switching behaviors are independent of product characteristics. Equation 8 generates price elasticities that are driven by consumer specific marginal utilities, θ^i. The random coefficient logit model captures consumer switching due to similarities in consumers tastes for product characteristics. Because consumers with similar tastes make similar choices, aggregating their individual responses yields market elasticities that appreciate product characteristics as determinants of switching behaviors. However, it is important to note that the random coefficients logit does not ameliorate IIA at the consumer level.

4.2 Bayesian Posterior Model Formulation

This research employs the method of Jiang et al. (2009) to simulate from the posterior of the random coefficient logit demand model. They demonstrate that their approach makes more efficient use of the data than the simulated generalized method of moments (GMM) approach typically implemented (Nevo, 2001). Efficient use of the data is important for our application because we investigate one market over 58 weeks for two leading brands and one store brand in each of four retailers. GMM approaches rely on estimation procedures that require optimization, often making search for optimal demand parameters difficult for some data sets. The difficultly in estimating globally or even locally optimal parameters is not due to a lack information in the data, rather the criterion function is irregular and not smooth owing to the inefficient use of data. The Bayesian

Markov Chain Monte Carlo (MCMC) methods used by Jiang et al. (2009) to estimate the random coefficient logit do not require optimization and are insensitive to simulation error. The tradeoff is to specify a distribution on the common demand shock. They show that their estimator performs well even when demand shock distribution is misspecified. In this subsection the likelihood is derived and the priors are introduced.

Recognizing the endogeneity of price I employ an instrumental variable approach. This requires specifying a recursive system containing the price and share equations. The price equation,

$$p_{jt} = Z_{jt}\delta + \xi_{jt}, \tag{13}$$

specifies price, p_{jt}, as a function of instrumental variables, Z_{jt}, and additive error, ξ_{jt}, where t indexes data observations. The share equation can be specified solely as a function of the aggregate shock $\eta_t = (\eta_{1t}, \ldots, \eta_{Jt})'$, given the distribution of θ^i and observed regressors $X_t = (X_{1t}, \ldots, X_{Jt})$. The density of shares can be written as a function of the demand shock density. The function relating demand shock to shares is given by $h(\cdot)$:

$$s_{jt} = h(\eta_t | X_t, \bar{\theta}, \Sigma). \tag{14}$$

Endogeneity of price implies that the random shocks ξ_{jt} are correlated with the demand shocks η_{jt} according to the following multivariate-normal density:

$$\begin{pmatrix} \xi_{jt} \\ \eta_{jt} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \Omega \equiv \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix} \right). \tag{15}$$

Up to this point the model is identical to that of Berry et al. (1995). The additional assumption necessary to specify the likelihood is a distributional assumption on the demand shock. The demand shocks are specified as independently distributed and homoscedastic. The joint density of share at time t is obtained using the change of variable theorem:

$$\begin{aligned}\pi(s_t, p_t|\bar{\theta}, \Sigma, \delta, \Omega) &= \pi(\xi_t, \eta_t|\bar{\theta}, \Sigma, \delta, \Omega) J_{\xi_t, \eta_t \to p_t, s_t} \\ &= \pi(\xi_t, \eta_t|\bar{\theta}, \Sigma, \delta, \Omega)(J_{p_t, s_t \to \xi_t, \eta_t})^{-1}. \end{aligned} \tag{16}$$

The likelihood is therefore given by:

$$L(\bar{\theta}, \Sigma, \tau^2) = \prod_t \pi(s_t, p_t|\bar{\theta}, \Sigma, \delta, \Omega). \tag{17}$$

The key to writing down the likelihood for this model is deriving the Jacobian,

$$J_{(p_t, s_t \to \xi_t, \eta_t)} = \left\| \begin{array}{cc} \nabla_{\xi_t} p_t & \nabla_{\eta_t} p_t \\ \nabla_{\xi_t} s_t & \nabla_{\eta_t} s_t \end{array} \right\| \tag{18}$$

where $\nabla_{\xi_t} p_t = I$ and $\nabla_{\eta_t} p_t = 0$. Consequently the Jacobian simplifies to:

$$\begin{aligned} J_{(p_t, s_t \to \xi_t, \eta_t)} &= \left\| \begin{array}{cc} I & \mathbf{0} \\ \nabla_{\xi_t} s_t & \nabla_{\eta_t} s_t \end{array} \right\| \\ &= \|\nabla_{\eta_t} s_t\| \end{aligned} \tag{19}$$

Which is the same as a model with out an endogenous regressor where:

$$\|\nabla_{\eta_t} s_t\| = \left\| \begin{bmatrix} \partial s_{1t}/\partial \eta_{1t} & \partial s_{1t}/\partial \eta_{2t} & \cdots & \partial s_{1t}/\partial \eta_{Jt} \\ \vdots & & & \\ \partial s_{Jt}/\partial \eta_{1t} & & \cdots & \partial s_{Jt}/\partial \eta_{Jt} \end{bmatrix} \right\|, \tag{20}$$

the matrix elements take the familiar following form:

$$\partial s_{jt}/\partial \eta_{kt} = \begin{cases} \int s_{ijt}(1 - s_{ijt}) \phi(\theta^i|\bar{\theta}, \Sigma) d\theta^i, & \text{for j=k;} \\ \int -s_{ijt} s_{ikt} \phi(\theta^i|\bar{\theta}, \Sigma) d\theta^i, & \text{otherwise.} \end{cases} \tag{21}$$

The likelihood stated in equation 13 is more explicitly written as:

$$L(\bar{\theta}, \Sigma, \tau^2) = \prod_t \left(J^{-1}(s_t, p_t, X_t, \Sigma) \prod_j \phi \left(\begin{bmatrix} \xi_{jt} = p_j t - Z_{jt}\delta \\ \eta_{jt} = h^{-1}(s_t | p_t, X_t, th\bar{e}ta, \Sigma) \end{bmatrix}, \Omega \right) \right) \quad (22)$$

Jiang et al. (2009) point out that in contrast to Berry (1994) and Nevo (2001) the Bayes approach properly accounts for uncertainty in the estimate of Σ. This is because the Bayesian MCMC approach alternates between drawing Σs from the posterior and inferring the remaining parameters given Σ. The recursive system is:

$$\begin{aligned} p_{jt} &= Z_{jt}\delta + \xi_{jt} \\ \mu_{jt} &= X_{jt}\bar{\beta} - \bar{\alpha} p_{jt} + \eta_{jt}, \end{aligned} \quad (23)$$

where the errors are distributed according to equation 15. The prior densities for $\bar{\beta}$ and $\bar{\alpha}$ are:

$$\begin{aligned} \bar{\delta} &\sim MVN(\bar{\delta}, V_{\bar{\delta}}) \\ \bar{\theta} &\sim MVN(\bar{\theta}, V_{\bar{\theta}}) \\ \Omega &\sim IW(\nu_0, V_\Omega). \end{aligned} \quad (24)$$

Where MVN denotes the multivariate normal density and IW denotes the inverted Wishart density, a multivariate generalization of the gamma distribution inverted.

To ensure positive definiteness, the random coefficient correlation matrix can be reparameterized in terms of the log of the diagonal elements of the Cholesky root.

$$\begin{aligned} \Sigma &= U'U \\ U &= \begin{pmatrix} e^{r_{11}} & r_{11} & \cdots & r_{1K} \\ 0 & e^{r_{22}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & r_{K-1,K} \\ 0 & \cdots & 0 & e^{r_{KK}} \end{pmatrix} \end{aligned} \quad (25)$$

where $r = \{r_{jk}\}_{j,k=1,\ldots,K,j\leq k}$. r's prior densities are

$$\begin{aligned} r_{jj} &\sim N(0, \sigma_{r\_jj}), && \text{for j=1,...,K;} \\ r_{jk} &\sim N(0, \sigma_{r\_off}), && \text{for j,k=1,...,K,j¡k.} \end{aligned} \tag{26}$$

All the priors I introduce are implemented with standard diffuse settings, the specific values used are presented in the next section on data, estimation, and results.

4.3 Supply Model Selection

In keeping with my estimation approach I formally rank the models of supply side conduct using Bayesian decision theory. This process allows me to rank the models and select the most probabilistic model. I begin by specifying models of channel pricing. Then I implement a Bayesian modeling approach to compute posterior model marginal densities, subsequently used for model selection.

The margins can be specified in a model of channel pricing as:

$$p_{jt} = RM_{jt} + MM_{jt} + \overbrace{Z_{jt}\gamma}^{ChannelCost} + \epsilon_{ijt}. \tag{27}$$

The implied price-cost margins for the six pricing games laid out in the previous section specify six competing models of channel pricing. The implied margins can be subtracted from both sides of equation 27 to define a channel cost specification for each pricing game:

$$p_{jt} - RM_{ijt} - MM_{ijt} = CC_{ijt} = Z_{jt}\gamma_i + \varepsilon_{ijt}. \tag{28}$$

This is the channel cost model for pricing game i. RM is the retail margin and MM is the manufacturer margin.

The channel pricing model specified in equation 24 parallels that of Villas-Boas (2007) and Bonnet and Dubois (2010). They estimate each channel cost model separately and conduct pairwise non-nested tests to identify the models that best explain the data generation process, which arguably are the most likely supply channel models. The non-nested tests they employ are not transitive. For example consider three possible models. If model 1 is chosen in favor of model 2 and 2 is chosen in favor of 3 it is not guaranteed that 1 is chosen in favor of 3.

Bayesian decision theory for model selection strictly ranks the models under consideration, bypassing the non-transitivity issue. If prior densities are the same for each model considered, Bayesian decision theory directs the researcher to select the most probabilistic model based on exact sample results. I compute posterior model probabilities directly and rank models from most to least probabilistic. I evaluate the model level error likelihoods under the following specification:

$$\begin{aligned} \varepsilon_{ijt} &= p_{jt} - RM_{jt} - MM_{jt} - Z_{jt}\tilde{\gamma}, \\ \varepsilon_{ijt} &\sim N(0, \kappa). \end{aligned} \tag{29}$$

Here $\tilde{\gamma}$ is the posterior estimate. My test exploits the temporal scedasticity within each panel of the cross section of models. Marginal density estimates are computed for the posterior error model in equation 28 to determine the best fitting pricing model.

5 Estimation and Model Selection Results

This section presents the specification of demand variables, demand parameter estimates, and results for the model selection exercise.

5.1 Specification, Estimation, and Parameter Estimates

To begin specification of the demand model market shares must be computed. To compute shares I assume that each member of Boston's population consumes 8 ounces of fluid milk each day.[4] Larger and smaller markets were considered but did not change elasticity estimates in a significant way, verifying the robustness of parameter estimates under different exogenously determined market sizes. Given actual consumption and total potential consumption one can compute the market share of the outside good as well as the shares for different brands of milk sold in the different chains. The Independent variables specified in the random coefficients logit demand equations product characteristics including: weighted price reduction, share of skim to whole, as well as food and non-food services that the supermarkets offered.

[4] 8 ounces is the recommended serving size for a glass of milk as stated on milk packaging

I employ the instrumental variable technique described in the previous section to identify α, the coefficient on the endogenous price variable. The price endogeneity control function specifies price as a function of channel input prices. The specification input prices considered are the price of raw milk multiplied by the brand indicator variables, price of electric, diesel, and retailer sales per square foot .[5]

We use diffuse prior setting for all model priors. All priors are proper, that is they have a probability measure of one over their support. All slope parameters have a prior mean of 0 and prior variance of $100 * I_k$, where I_k is an identity matrix of dimension k, equal to the number of slope parameters. Recall that error variance Ω has an inverted Wishart density with:

$$\nu_0 = k + 1 \text{ and } V_\Omega = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix} \tag{30}$$

The prior setting for r, the demand parameter covariance matrix elements have mean 0 and variance:

$$\sigma^2_{r_j j} = \frac{1}{4} log \left(\frac{1 + \sqrt{1 - 4(2(j-1)\sigma^4_{r_o ff} - c)}}{2} \right), \tag{31}$$

where $\sigma^2_{r_o ff} = 1$ and $c = 50$. This specification of priors for r ensures that the priors associated with the correlations are uniformly distributed between 0 and 1 (Jiang et al., 2009, p.146-147).

Table 4 presents market mean parameter estimates, $\bar{\theta}$, standard deviation of the posterior distribution of $\bar{\theta}$ and numerical standard errors for the distribution estimates for the simple logit and random coefficient logit demand model. Simulation of the market share integral for the random coefficients logit from equation 11 is achieved by simulating 100 households, the literature commonly uses between 50 and 100 households. Jiang et al. (2009) document that the Bayes sampling properties are virtually unchanged when increasing the number of households from 50 to 200.

Here we discuss the random coefficients logit demand coefficients. The marginal utility of income parameter on price has the proper sign, adhering to the law of demand. The price reduction coefficient is located near zero indicating that price promotions have no major impact on average

[5] Interacting raw milk prices with brand dummies allows us to separate brand variation in prices (Villas-Boas, 2007, p.637-38).

consumption utility. The positive units per volume coefficient indicates that consumers prefer smaller packaging per unit. The positive skim to whole ratio testifies that consumer prefer milk with less fat on average. More services generate higher utility whether they are food or non-food services. Below the demand parameter estimates appear estimates for the price endogeneity control function and below them appear average estimates of error covariance.

Table 5 displays the average estimates for the covariance of θ_i, Σ, over the individuals in the market. Variance estimates on the main diagonal of this matrix suggest there is a wide range of preferences over package size as evidenced by a variance measure of more than 18. The variance of nearly 79 on the food service marginal utility parameter suggest that a sizeable portion of consumers in fact negatively value food service. The price coefficient has a standard deviation of approximately 7. Since the marginal distribution of the price parameter is centered about -43.395 effectively all of the consumers in the market obey the law of demand. The fact that the highest degree of covariance is between price and other product characteristics supports the notion that adjusting the product, place, and promotion is an effective marketing technique to attract consumers who are less sensitive to price.

5.2 Supply Model Test Results

Table 7 displays results from the set of channel marginal cost models introduced in section 3. Coefficients on other regressors measure channel marginal costs sensitivity to changes in input prices. Log marginal density estimates at the bottom of the table reveal that the channel pricing game characterized by model 6 is the best fitting model. Recall from section 3 that model 6 seemed most plausible ex ante based on a stylized assessment of Boston's milk market. Given both forms of analysis is stands to reason that model 6 best characterizes the market, and it establishes a baseline from which to compare counterfactual market structures.

6 Counterfactual Simulation Analysis

The structural models of demand and supply are used in this section to conduct three counterfactual simulations. I begin by introducing the simulation technique. Next I describe the counterfactuals.

Then I present the results of our simulations.

6.1 Technique

Given estimates of the structural parameters, ownership matrices, response matrices, market share, and implied channel costs, equilibrium prices, p_t^*, are determined by the following system of equations:

$$p_t^* = M(T_r, T_w, \triangle_{rt}, \triangle_{wt}, s_t(p_t^*)) + C_t. \tag{32}$$

Where $M(\cdot)$ denotes the implied model for channel margins, $C_t \equiv p_t - M(\ldots, s_t(p_t)$ is channel costs, and p_t are observed prices. Counterfactual equilibria arise under alternative pricing games. I determine the counterfactual equilibrium prices and shares, $s_t(p_t^*)$, by specifying the appropriate counterfactual ownership matrices, T_r and T_w, and response matrices,$\triangle_{rt}$ and $\triangle_{wt}$.

Given equilibrium prices that arise under a particular pricing game the change in consumer surplus, $CS_t(p_t) - CS_t(p_t^*)$, is evaluated using the following formula for the random coefficients logit demand model:

$$CS_{it}(p_t) = \frac{1}{|\alpha_i|}\mathbb{E}\left[max_j V_{ijt}(p_t)\right] = \frac{1}{|\alpha_i|} ln\left(\sum_{j=1}^{J} exp[V_{ijt}(p_t)]\right). \tag{33}$$

For the counterfactual games I evaluate firm specific margins are not always identified since I don't model the bargaining that occurs between retailers and manufacturers on nonlinear contracts and I do not observe wholesale prices.

6.2 Counterfactuals

In the previous section Bayesian decision theory selects model six as most appropriate for this data sample. Recall that model six has Stop & Shop integrated into its store brand production and brand manufacturers Garelick and Hood set wholesale price as Stackelberg leaders, the remaining retailers coordinate with the brand manufacturers. I simulate changes in price, market share, and consumer surplus in the equilibrium framework described above, for three counterfactual scenarios.

The first counterfactual scenario I evaluate is the divestiture of Stop & Shop store brand processing where they subsequently engage in a nonlinear contract with brand manufacturers as other retailers were doing.

The second and third counterfactuals I evaluate are markets without store brands. In one scenario all supermarkets make nonlinear contracts. In scenario two retailers and manufacturers maximize profits independently with manufacturers as Stackelberg leaders. This is the double marginalization outcome the presence of store brands has been credited with eliminating (Mills, 1995; Steiner, 2004). These two counterfactuals reveal the extent to which store brand presence improves consumer welfare.

6.3 Results

Table 8 documents average percent changes in price, channel profits, market share, and consumer surplus under each counterfactual. Sample standard deviation and sample standard error appear beside each estimate of the mean change. Under scenario one Stop & Shop's impending divestiture promises to decrease prices on all fluid milks across the board. The steepest decline in price happens in Stop & Shop for the brand milks. The Stop & Shop store brand increases in price, this result suggests the effects of coordination are at work to increase the flow of profits to manufacturers from milks sold in Stop & Shop. Changes in market share also testify to this fact owing to major increases in the market shares of brand products at Stop & Shop, and a smaller decline in share at other retailers. Ultimately, Stop & Shop's divestiture of it's processing plant results in a small average net increase in consumer surplus.

The lower panels of table 8 display changes for the second and third scenarios. Under the second scenario elimination of double marginalization through the Stop & Shop marketing channel decreases prices on brand milks sold at Stop & Shop. However the net increase in prices across all retailers results in an overall decrease in consumer surplus. If one believes that without store brands the market would be characterized by double marginalization the third panel of table 9 offers the equilibrium differential. This grim possibility attests that prices would be higher across the board and that consumer surplus would be dashed by nearly 94%.

7 Conclusion

This paper conducts an empirical examination of store brand marketing on vertical competition among retailers and manufacturers. Estimating market demand provides parameter estimates used to calculate channel profit margins under six alternative channel pricing games. From the channel profit margins estimated we derived six alternative channel marginal costs models corresponding to each supply channel pricing game. The model we determined to be most probable posits that Stop & Shop was integrated into its own store brand processing and procured branded milks from manufacturers who were setting wholesale prices to Stop & Shop as channel Stackelberg leaders while the other retailers coordinated channel pricing with manufacturers. This result is consistent with our institutional understanding of the Boston milk marketing channel.

Simulations found that Stop & Shop's divestiture of its store brand milk processing to the brand manufacturers likely lowered prices on all milks except Stop & Shop store brand resulting in a marginal consumer welfare increase. Results also indicated that if store brands were not in the market and the market was coordinated, prices would be higher at all retailers but Stop & Shop and Consumer surplus would fall by nearly 30%. If store brands were absent from the market, and double marginalization pricing emerged, prices increase across the board and consumer surplus is dashed by nearly 94%.

Should post divesture data from the Boston milk market become available one can test for structural changes in the market. Ultimately, availability of wholesale prices would enable one to formally test the identification strategy used for model selection. It would also enable the researcher to identify the transfer payments retailers make to brand manufacturers in the form of channel coordinated wholesale price.

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Table 1: Market Shares, Within Retailer Share, Prices: Summary Statistics

Retailer		Manufacturer	Mean	S.D.	Minimum	Maximum
Market Share	*Chain Share*					
Stop&Shop	0.180	Hood	0.022	0.005	0.013	0.029
		Garelick	0.032	0.003	0.026	0.038
		Store Brand	0.126	0.006	0.112	0.140
Shaws	0.137	Hood	0.009	0.007	0.000	0.017
		Garelick	0.030	0.006	0.017	0.040
		Store Brand	0.097	0.011	0.073	0.117
Demoulas	0.123	Hood	0.006	0.002	0.003	0.011
		Garelick	0.007	0.003	0.003	0.011
		Store Brand	0.111	0.010	0.090	0.131
Star	0.082	Hood	0.013	0.003	0.008	0.018
		Garelick	0.026	0.003	0.017	0.032
		Store Brand	0.043	0.007	0.029	0.053
Group Share						
Stop&Shop	0.180	Hood	0.121	0.023	0.076	0.159
		Garelick	0.180	0.017	0.147	0.227
		Store Brand	0.699	0.017	0.661	0.746
Shaws	0.137	Hood	0.070	0.052	0.000	0.134
		Garelick	0.221	0.030	0.164	0.274
		Store Brand	0.709	0.037	0.633	0.764
Demoulas	0.123	Hood	0.048	0.022	0.024	0.094
		Garelick	0.053	0.025	0.025	0.093
		Store Brand	0.898	0.045	0.832	0.949
Star	0.082	Hood	0.162	0.043	0.099	0.236
		Garelick	0.316	0.018	0.279	0.356
		Store Brand	0.523	0.044	0.448	0.604
Price per gallon						
Stop&Shop	0.180	Hood	$2.772	$0.113	$2.460	$2.961
		Garelick	$2.731	$0.207	$2.363	$3.072
		Store Brand	$2.436	$0.117	$2.251	$2.685
Shaws	0.137	Hood	$2.765	$0.151	$2.408	$3.087
		Garelick	$2.708	$0.181	$2.426	$3.058
		Store Brand	$2.395	$0.126	$2.207	$2.651
Demoulas	0.123	Hood	$2.776	$0.077	$2.597	$2.924
		Garelick	$2.646	$0.135	$2.380	$2.935
		Store Brand	$2.211	$0.101	$2.054	$2.411
Star	0.082	Hood	$2.925	$0.091	$2.761	$3.143
		Garelick	$2.786	$0.156	$2.567	$3.168
		Store Brand	$2.434	$0.134	$2.236	$2.723

Source: IRI

Table 2: Promotion, Package Size, Skim to Whole Ratio: Summary Statistics

Retailer	Manufacturer	Mean	Median	S.D.	Minimum	Maximum
Weighted Price Reduction						
Stop&Shop	Hood	8.33	7.78	5.30	0	22.89
	Garelick	8.99	7.48	6.59	0	27.37
	Store Brand	8.29	8.30	3.19	0	16.68
Shaws	Hood	7.42	8.29	7.17	0	26.83
	Garelick	11.48	12.18	5.54	0	24.89
	Store Brand	8.04	8.50	4.34	0	19.22
Demoulas	Hood	1.86	0.00	3.00	0	7.00
	Garelick	2.08	0.00	3.16	0	11.16
	Store Brand	4.17	4.94	3.74	0	11.95
Star	Hood	7.65	7.32	4.16	0	17.03
	Garelick	9.41	9.47	4.51	0	21.05
	Store Brand	5.50	5.93	3.23	0	12.75
Units per Volume						
Stop&Shop	Hood	0.187	0.186	0.009	0.175	0.227
	Garelick	0.187	0.186	0.006	0.175	0.213
	Store Brand	0.171	0.172	0.004	0.157	0.178
Shaws	Hood	0.199	0.199	0.005	0.185	0.209
	Garelick	0.158	0.158	0.002	0.154	0.163
	Store Brand	0.277	0.264	0.026	0.239	0.318
Demoulas	Hood	0.236	0.239	0.018	0.192	0.278
	Garelick	0.154	0.157	0.005	0.147	0.162
	Store Brand	0.288	0.292	0.013	0.265	0.306
Star	Hood	0.201	0.201	0.006	0.185	0.214
	Garelick	0.165	0.166	0.002	0.160	0.172
	Store Brand	0.270	0.265	0.015	0.247	0.295
Skim to Whole Ratio						
Stop&Shop	Hood	12.52	12.16	1.85	7.69	17.92
	Garelick	16.53	16.31	2.13	11.11	22.08
	Store Brand	10.73	10.75	0.33	9.99	11.61
Shaws	Hood	7.17	8.66	3.22	1.06	10.69
	Garelick	14.32	14.23	2.04	11.35	18.45
	Store Brand	11.57	11.47	0.70	10.25	12.73
Demoulas	Hood	4.20	4.20	1.29	2.10	6.28
	Garelick	4.19	4.07	0.83	2.96	7.46
	Store Brand	12.47	12.43	0.38	11.80	13.54
Star	Hood	8.53	8.93	2.39	4.94	14.41
	Garelick	14.13	13.77	2.16	10.45	20.73
	Store Brand	11.56	11.73	0.81	9.16	14.23

Source: IRI

Table 3: Income, Services, Cost Proxies and Input Costs: Summary Statistics

Retailer	Variable	Mean	Median	S.D.	Minimum	Maximum
	Income	$18,003	$17,894	$1,398	$16,240	$19,787
Stop&Shop	Number of stores	69.65	70.5	4.40	61	74
	Bakery	0.861	0.888	0.056	0.730	0.904
	Bank	0.578	0.605	0.053	0.453	0.622
	Restaurant	0.043	0.054	0.017	0.015	0.057
	Pharmacy	0.567	0.599	0.075	0.423	0.649
	Seafood Counter	0.947	0.957	0.032	0.880	0.990
	Volume Sales	491559	509857	41520	426689	553425
	Retial Sq Footage	41178	42234	3293	33932	44730
Shaws	Number of stores	46.45	46	1.61	43	49
	Bakery	0.924	1	0.123	0.708	1
	Bank	0.391	0.391	0.059	0.313	0.486
	Restaurant	0.064	0.066	0.048	0	0.136
	Pharmacy	0.055	0.043	0.026	0.019	0.093
	Seafood Counter	1	1	0	1	1
	Volume Sales	35388	36149	2528	30125	38111
	Retial Sq Footage	24991	24903	355	24465	25558
Demoulas	Number of stores	32.1	32	0.31	32	33
	Bakery	0.544	0.588	0.093	0.352	0.633
	Bank	0.046	0.000	0.064	0.000	0.156
	Restaurant	0.055	0.062	0.013	0.031	0.063
	Pharmacy	0.017	0.000	0.028	0.000	0.063
	Seafood Counter	0.829	0.882	0.102	0.641	0.917
	Volume Sales	555204	566927	32652	497656	598438
	Retial Sq Footage	38641	40026	5496	27087	44781
Star	Number of stores	39.25	39.5	2.75	33	42
	Bakery	0.978	1	0.032	0.920	1
	Bank	0.365	0.383	0.059	0.244	0.429
	Restaurant	0.180	0.173	0.078	0.095	0.360
	Pharmacy	0.370	0.382	0.047	0.273	0.424
	Seafood Counter	0.971	0.970	0.019	0.945	1
	Volume Sales	405614	419367	35431	327000	435888
	Retial Sq Footage	35260	34617	2756	32196	41819
	Costs					
	Price of raw Milk	$1.40	$1.39	$0.10	$1.23	$1.66
	Electric	$7.67	$7.86	$0.93	$5.19	$9.27
	Diesel	$112.42	$113.21	$12.23	$89.33	$131.72

Source: Income: Market Scope, Retailer Characteristics: Spectra Marketing,
Costs: Federal Milk Market Order and Energy Information Association

Table 4: Posterior Model Mean Parameter Estimates

Variable	Logit coefficient	Logit s.d.	Logit n.s.e.	Random Coefficients Logit coefficient	Random Coefficients Logit s.d.	Random Coefficients Logit n.s.e.
Demand						
price	-33.000	2.000	0.0150	-43.395	4.557	0.5011
price reduction	0.001	0.005	0.0000	-0.006	0.014	0.0018
units per volume	3.464	0.648	0.0043	3.720	1.487	0.1470
skim to whole ratio	-7.963	0.264	0.0017	0.093	0.030	0.0042
food service	1.715	0.200	0.0015	2.142	0.615	0.0764
non food service	-0.597	0.470	0.0037	4.123	1.237	0.1524
constant	2.475	0.418	0.0030	3.477	2.298	0.2105
Price						
constant	0.1900	0.0350	0.0003	0.1900	0.0467	0.0022
price raw hood	0.0190	0.0174	0.0001	0.0160	0.0174	0.0003
price raw garelick	0.0150	0.0174	0.0001	0.0110	0.0174	0.0003
price raw store brand	-0.0009	0.0174	0.0001	-0.0051	0.0174	0.0003
electric	-0.0054	0.0016	0.0000	-0.0048	0.0018	0.0000
diesel	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000
Error Covariance						
Ω_{11}	0.0015	0.0001	0.0000	0.0031	0.0230	0.0015
Ω_{12}	0.0000	0.0003	0.0000	0.0718	0.9900	0.0664
Ω_{22}	0.0340	0.0018	0.0000	3.8673	42.4090	2.9443

Source: Author's Calculations

Table 5: Posterior Model Demand Parameter Mean Covariance Estimates

	constant	price reduction	units per volume	skim to whole	food service	non food service	price
constant	0.545	-0.012	0.605	0.062	-2.495	-0.230	-1.296
price reduction	-0.012	0.030	-0.160	-0.003	-0.129	-0.129	0.178
units per volume	0.605	-0.160	18.010	0.054	2.765	-0.921	3.053
skim to whole	0.062	-0.003	0.054	0.086	-0.564	-0.133	0.287
food service	-2.495	-0.129	2.765	-0.564	78.963	-3.217	5.453
non food service	-0.230	-0.129	-0.921	-0.133	-3.217	6.244	-9.534
price	-1.296	0.178	3.053	0.287	5.453	-9.534	41.784

Source: Author's Calculations

Table 6: Posterior Model Mean Demand Elasticity Estimates

	SS Hood	SS Gar	SS SB	D Hood	D Gar	D SB	Sh Hood	Sh Gar	Sh SB	St Hood	St Gar	ST SB
SS Hood	-6.816	0.055	1.274	0.274	0.160	0.431	0.236	0.157	1.378	0.157	0.187	0.283
SS Gar	0.156	-6.640	0.870	0.351	0.175	0.359	0.280	0.161	0.974	0.163	0.190	0.303
SS SB	0.096	0.023	-3.154	0.226	0.222	0.706	0.155	0.163	1.154	0.094	0.113	0.209
D Hood	0.059	0.027	0.646	-5.646	0.637	0.727	0.702	0.357	0.331	0.228	0.322	0.428
D Gar	0.054	0.021	0.997	1.000	-6.260	0.867	0.549	0.368	0.485	0.194	0.267	0.405
D SB	0.075	0.022	1.631	0.587	0.446	-5.458	0.374	0.300	0.890	0.169	0.220	0.366
Sh Hood	0.053	0.022	0.464	0.731	0.364	0.483	-6.729	0.370	0.598	0.413	0.569	0.774
Sh Gar	0.053	0.019	0.729	0.559	0.367	0.581	0.556	-6.837	0.876	0.352	0.462	0.740
Sh SB	0.113	0.028	1.253	0.126	0.117	0.419	0.218	0.212	-4.523	0.250	0.283	0.555
St Hood	0.027	0.010	0.213	0.181	0.098	0.166	0.314	0.178	0.521	-5.584	1.225	1.657
St Gar	0.025	0.009	0.200	0.200	0.105	0.169	0.338	0.183	0.462	0.958	-5.115	1.666
St SB	0.026	0.010	0.252	0.180	0.109	0.191	0.313	0.199	0.616	0.882	1.134	-4.198

Note: Cell i,j, where i indexes row and j indexes columns, gives the percent change in market share for brand i for a one percent change in the price of brand j

Note: Stop & Shop, Demoulas, Shaws, and Star Market are indicated by SS, D, Sh, and St respectively.

Source: Author's calculations

Table 7: Posterior Model Channel Marginal Costs and Log Marginal Density Estimates

Variable		Model1	Model2	Model3	Model4	Model5	Model6
price raw hood	coefficient	0.025	0.016	0.00624	0.018	0.04633	0.01702
	s.d.	0.0128	0.0120	0.0139	0.0084	0.0234	0.0086
	n.s.e	9.4E-05	8.9E-05	1.1E-04	5.9E-04	1.8E-04	6.3E-05
price raw garelick	coefficient	0.0079	-0.0011	-0.007	0.013	0.00949	0.01177
	s.d.	0.0128	0.0120	0.0139	0.0084	0.0234	0.0086
	n.s.e	9.4E-05	8.9E-05	1.1E-04	6.0E-04	1.8E-04	6.2E-05
price raw store brand	coefficient	-0.01	0.016	0.02113	-0.017	0.02492	0.00163
	s.d.	0.0128	0.0120	0.0139	0.0084	0.0234	0.0086
	n.s.e	9.4E-05	8.9E-05	1.1E-04	6.0E-04	1.8E-04	6.4E-05
electric	coefficient	-0.0066	-0.0081	-0.00915	-0.005	-0.02523	-0.00497
	s.d.	0.0012	0.0011	0.0013	0.0008	0.0022	0.0008
	n.s.e	9.3E-06	7.6E-06	9.5E-06	6.1E-06	1.6E-05	5.9E-06
diesel	coefficient	-0.000018	-0.000029	-0.00011	0.000064	-0.00015	0.00007
	s.d.	0.0001	0.0001	0.0001	0.0007	0.0002	0.0001
	n.s.e	7.5E-07	7.8E-07	8.8E-07	5.0E-07	1.3E-06	5.2E-07
constant	coefficient	0.1239	0.1485	0.1587	0.1391	0.0659	0.1338
	s.d.	0.6186	0.6186	0.6186	0.6186	0.6186	0.6186
	n.s.e	4.5E-03	4.4E-03	4.4E-03	4.4E-03	4.5E-03	4.4E-03
Log Marginal Density		-698.359	-698.646	-699.218	-698.198	-701.450	$-698.09^{\star}$

Note: $\star$ indicates the model selected based on posterior marginal density estimates.
Source Author's Calculations

Table 8: Simulation Results

	% Change in Price			% Change in Channel Profit			% Change in Market Share		
	mean	s.d.	s.e.	mean	s.d.	s.e.	mean	s.d.	s.e.
Stop & Shop divestiture									
SS Hood	-14.25	0.85	0.111	0.472	0.080	0.010	149.86	5.92	0.777
SS Gar	-14.44	1.01	0.132	0.456	0.059	0.007	148.96	6.15	0.807
SS SB	0.39	0.09	0.012	-0.030	0.007	0.000	-4.29	0.93	0.122
% Change in Category Channel Profit				0.034	0.015	0.001			
D Hood	-0.24	0.19	0.026	-0.047	0.030	0.003	-3.65	2.64	0.347
D Gar	-0.13	0.15	0.020	-0.015	0.013	0.002	-1.03	0.77	0.102
D SB	-0.15	0.14	0.019	-0.024	0.008	0.001	-1.80	0.56	0.074
% Change in Category Channel Profit				-0.020	0.009	0.001			
Sh Hood	-0.09	0.05	0.006	-0.034	0.013	0.002	-2.88	1.18	0.155
Sh Gar	-0.05	0.03	0.004	-0.015	0.007	0.001	-1.22	0.61	0.080
Sh SB	-0.13	0.10	0.013	-0.029	0.009	0.001	-2.27	0.68	0.089
% Change in Category Channel Profit				-0.023	0.007	0.001			
St Hood	-0.08	0.11	0.014	-0.015	0.006	0.001	-1.26	0.54	0.071
St Gar	-0.06	0.06	0.008	-0.008	0.003	0.001	-0.66	0.30	0.039
ST SB	-0.13	0.09	0.012	-0.016	0.005	0.001	-1.26	0.42	0.055
% Change in Category Channel Profit				-0.011	0.004	0.001			
% Change in Consumer Surplus							0.04	0.23	0.030
No store brand in market: channel coordination									
SS Hood	-15.83	1.78	0.233	2.532	1.038	0.136	549.16	192.78	25.314
SS Gar	-15.92	1.74	0.229	2.208	0.525	0.069	490.42	93.47	12.273
D Hood	1.52	1.62	0.213	1.265	0.683	0.090	111.14	61.60	8.088
D Gar	3.24	2.13	0.279	1.492	0.991	0.130	119.05	86.54	11.364
Sh Hood	0.34	0.97	0.127	1.236	0.509	0.067	120.14	51.68	6.786
Sh Gar	0.90	1.63	0.214	1.493	0.740	0.097	139.48	70.79	9.295
St Hood	4.28	1.77	0.232	0.780	0.244	0.032	59.98	23.07	3.029
St Gar	4.93	1.96	0.258	0.698	0.312	0.041	50.97	26.80	3.519
% Change in Consumer Surplus							-28.01	18.61	2.444
No store brand in market: double marginalization									
SS Hood	6.92	1.96	0.257	4.356	1.120	0.147	347.83	100.54	13.202
SS Gar	8.46	4.14	0.543	3.844	0.704	0.092	293.95	76.36	10.027
D Hood	24.90	5.64	0.740	3.549	1.969	0.259	109.20	96.63	12.688
D Gar	42.54	11.69	1.535	2.897	1.770	0.232	42.03	68.80	9.034
Sh Hood	24.25	2.29	0.301	3.818	1.179	0.155	96.13	44.57	5.853
Sh Gar	36.52	9.07	1.190	3.977	1.599	0.210	68.73	55.64	7.306
St Hood	34.27	6.08	0.799	2.286	0.940	0.123	73.19	50.09	6.577
St Gar	49.88	13.13	1.724	1.051	0.473	0.062	-6.76	25.04	3.288
% Change in Consumer Surplus							-93.67	17.32	2.274

Source: Author's calculations

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